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METHODOLOGY TO QUANTIFY THE POTENTIAL NET ECONOMIC CONSEQUENCES--ETC(U)

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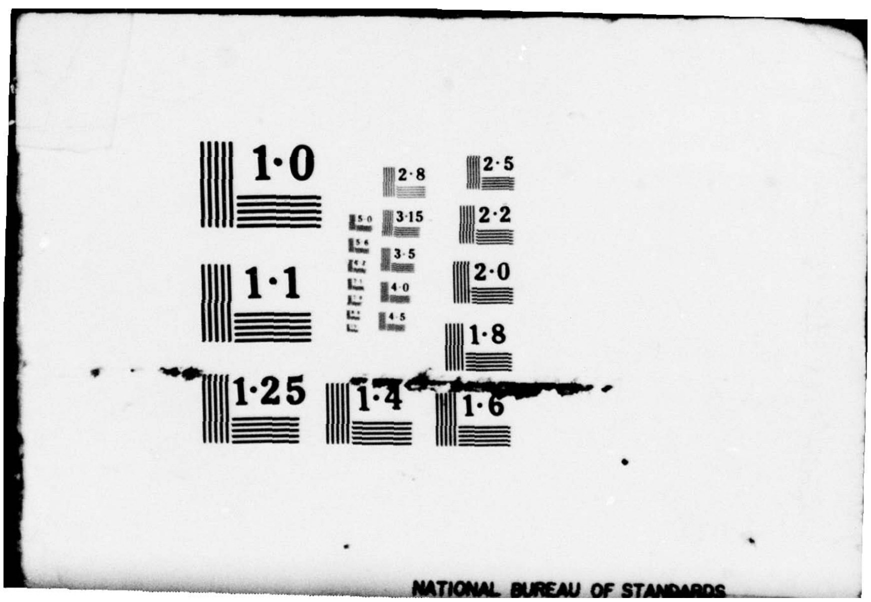
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REPORT

VOLUME II (Appendix II)

Methodology to Quantify the Potential Net Economic Consequences of Increased NATO Commonality, Standardization and Specialization

Prepared for:

The International Economic Affairs Directorate
Office of the Assistant Secretary of Defense
International Security Affairs

In response to:

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By:

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Potomac, Maryland 20854

as

Sub-contractor to:

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METHODOLOGY TO QUANTIFY THE POTENTIAL NET ECONOMIC CONSEQUENCES OF INCREASED NATO COMMONALITY, STANDARDIZATION AND SPECIALIZATION

Prepared for:

The International Economic Affairs Directorate
Office of the Assistant Secretary of Defense
International Security Affairs

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This study defines and demonstrates interrelated methodologies for estimating the costs of cooperative NATO weapons systems production programs for (a) individual programs (the MICRO methodology) and (b) NATO Alliance member nations (the MACRO methodology). The MICRO methodology is based on standard cost estimating techniques and requires detailed input data concerning production factors. The MACRO methodology relies on production data from analogous industrial (OVER)

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(20) Abstract

activities in combination with gross expected major system acquisitions to estimate gross economies available to the Alliance from utilization of least cost production option. Cost estimates derived by both MICRO and MACRO methodologies are for demonstration purposes only.

SCALE ECONOMIES AND LEARNING CURVES:

A REVIEW OF THE U.S. EVIDENCE WITH SPECIAL REFERENCE TO MILITARY COSTS

BY

Benjamin P. Klotz

C & L Associates
Washington, D.C.
June 28, 1978

INTRODUCTION

Resistance to rising military spending has stimulated renewed interest in the potential cost savings achievable from more standardization and specialization in weapons production for the NATO nations. Currently, several different weapons are produced in various NATO countries to do roughly the same job. This not only wastes money by requiring essentially duplicate programs of research and development but it also foregoes the opportunity to lower unit costs by engaging in longer production runs of a weapon of a common type. The fragmentation of weapons shortens production runs and bypasses the chance to achieve economies of scale in production and to learn from the experience gained from repetition. In addition, some common weapons (such as the F-16 combat aircraft) are produced in several nations, also foregoing the chance to achieve economies of scale and learning in production.

This study surveys the literature on scale economies and learning in production to develop the basic information needed to assess the potential cost savings resulting from a rationalization and reshuffling of weapons production to the nations with the lowest cost of production. That is, ~~we wish to construct~~ a framework is contructed to measure the savings from specialization and division of labor in the production of military products. We do not, however, address the question of potential savings in research and development expenditures, or in life-cycle

logistics costs for weapons. Nor do we consider the extent to which common weapons would increase military effectiveness.

It is generally agreed that unit costs of production fall as output expands. In the following sections we discuss the two theories, scale economies and learning-from experience, usually presented to explain this fall in costs, critically evaluate the evidence on the magnitude the fall, and use the evidence to suggest a framework for estimating the cost savings achievable from more specialization among nations in weapons production for NATO.

THEORIES ABOUT ECONOMIES OF SCALE AND LEARNING IN PRODUCTION

ECONOMIES OF SCALE

It is convenient to express input-output relations in the form of a production function. Given the level of technology, output can be written as

$$(1) \quad Q = F(L, K, M)$$

where Q is output produced in a period of time, say a year; L is the flow of labor services; K, the flow of capital services, and M is the flow of other inputs, say materials. In more sophisticated versions inputs are disaggregated into different types of labor and capital. Equation (1) most naturally refers to plant production, at which level inputs and the resulting outputs can be related by engineering relations. Economies of scale occur in (1) if, when all inputs are increased by x percent, output rises by more than x percent. This allows unit costs of production to fall as output expands, assuming input prices remain fixed. Textbooks often assume unit cost curves are U-shaped with unit (i.e., total average) costs falling to some level as output expands and then rising again as the level of production is increased even further. There is no necessity, however, for production to ever reach the region of increasing costs in

practice. It is a notional region that is "out there" as a warning to the overly ambitious entrepreneur.

Economies of scale could occur for several reasons. One input, such as managerial skill or entrepreneurial activity, may be indivisible so that it is constant at all output levels. It is therefore used more efficiently as output expands, at least up to the point of minimum cost. Some theorists regard this argument as a cheat, however, since it predicts economies of scale precisely because it does not allow all inputs (comprehensively defined) to increase in the same proportion. A perhaps better argument for scale economies is that more efficient machines, selected from an existing array of blueprints for alternatives, can be employed at higher levels of production. For example, the output of, say, blast furnaces may be proprotional to their volume while their capital inputs may be proportional to their surface. The surface-volume relation of spheres and cylinders creates a presumption in favor of economies of scale, at least over certain ranges of output [Haldi and Whitcomb; Bruni].

Because economies of scale cause unit costs to fall we can write

$$(2) \quad Y = f(Q)$$

where Y is average total costs. This relation could be specialized to

$$(3) \quad Y = a\,Q^{b}$$

where a and b are constants (b, the elasticity of unit costs to output, being negative). Both (2) and (3) assume input prices are fixed as output Q expands. In practice, this may not occur because plant expansion, and the attendant increase in the demand for inputs, may drive up their

prices. This will occur unless the supply of inputs is perfectly elastic to the expanding plant. Rising input prices, of course, tend to offset cost savings achieved by exploiting economies of scale. So, if we apply the above argument to an *industry*, rising input prices are more likely to occur than if only one plant expands, and unit costs may not fall despite economies of scale at the plant level.

A similar argument can be employed if a *firm* (a collection of plants under one control) expands. Administrative complexity may cause rising costs to the firm despite technical economies of scale at the plant level, if production is spread over a number of plants. Producing on different sites causes problems of administrative complexity and co-ordination (an excellent example of this is international co-operative ventures in aerospace projects, such as Roland, the F-15 and the F-16 combat aircraft).

LEARNING BY DOING

The production and cost function approach, expressed in (1) and (2), is static because it does not allow costs to fall with the experience gained in production. By abstracting from technical change, or by assuming technical change is exogenous (unrelated to the present or past pattern of production), the static approach risks missing much of the theoretically interesting features of production through time. In fact, technical change may well be endogenous, with the efficiency with which inputs are used depending on the experience gained by a plant through its past volume of production of a project. In this case, (2) can be altered to read

(4) $Y = f(X)$

where X is the cumulative output produced by the plant in the past. That is, X is the length of the production run to date. A more specialized version is

$$(5) \quad Y = a\,X^{b}$$

In this long-linear learning-curve formula, a and b are constants (with b, the elasticity of unit costs to cumulative output, being negative).

In various applications, Y might stand for total unit costs, or unit labor costs, or unit capital costs, or even unit material costs. When separate curves are fitted for each input the aggregate curve (for total unit costs) is a weighted average of the individual input curves, with the weights being the input shares in total costs. Of course these shares will change as X increases, unless the b is the same for each input.

Function (4) can also vary depending on the product in question, with little learning to be expected in plants specializing in routine assemblyline operations where X has reached the, say, 100,000 level. However, Baloff has argued that learning takes place even after, and apart from, worker familiarity with the mechanical tasks of production. He stresses new ways can constantly be found to reorganize the work flow more efficiently, and new techniques of production (perhaps embodied in new capital equipment) are constantly being invented. These continued novelties could maintain learning effects even after very long production runs.

The relation between cost functions and learning has been discussed by Oi and by Preston and Keachie. An obvious generalization would be to allow the level of technology, _a_, in (3) to reflect the learning phenomenon in (5) so that we can write

(6) $Y = a X^{b} Q^{b'}$

where _b_ and _b_' need not be equal. Sheshinsky has tried something like this, in concept, using U.S. data for a test.

An alternative learning function would relate the _percentage change_ in unit costs to the _percentage change_ in cumulative output, thus converting the variables in (5) into a linear equation in logarithmic first-differences (these being equal to percentage changes for small variations). Theoretically, this transformation is trivial, but it makes a great deal of difference (as we will argue in the next section) when choosing how to go about estimating (5) and then interpreting the results. In a nutshell the problem is that, if a percentage-change relation is true and if it is plagued by random measurement errors (as is likely), then (5), being the cumulation of percentage changes, will exhibit a highly correlated sequence of measurement errors (they being the cumulation of random errors) through time. This cumulation invalidates the use of ordinary least squares to measure (5). Instead, generalized least squares should be used to allow for the suspected serial correlation (Theil).

A last complication is that Y could stand for either average, or marginal, unit costs. However, estimated _b_ would be about the same in either case once cumulative output X exceeds about 30 units of production (Hartley).

EVIDENCE ON SCALE AND LEARNING IN PRODUCTION

ESTIMATES OF ECONOMIES OF SCALE

Economists and engineers have both addressed the problem of measuring the extent of economies of scale in industry. Most studies have focussed on the analysis of industry aggregates, however, rather than upon the more proper data generated by firm and plant operations. The main body of econometric studies of production have regressed value added, a measure of output, against the two inputs, labor and capital. Other approaches have fitted engineering production functions, cost functions, and even short-run demand curves for labor in order to get at scale questions. Less rigorous, but perhaps more useful, investigations have adopted the so-called survivor method to find the size that is most efficient by a process of natural selection. Finally, the most reliable, but probably too limited, method has been simply to interview businessmen in various industries and ask them to predict the fall in unit costs if output were to expand by specified quantities. This last method has been favored by students of industrial organization, as opposed to the econometric production-function approach favored by the general economic theorist.

Since the original study by Cobb and Douglas literally hundreds of economists have tried their hand at regressing a measure of output against measures of labor and capital inputs. Several surveys of this literature have been conducted (Walters, 1963; Nerlove, 1967; Jorgenson, 1975; Teitel, 1975).

For studies that define output as value added and define inputs as the flow of labor and capital services (i.e., manhours and capital stock multiplied by a utilization factor) the results are appallingly monotonous: Almost all industries in which Cobb-Douglas or Constant-Elasticity-of-Substitution production functions have been fitted exhibit constant returns to scale. That is, the sum of the output elasticity with respect to labor and capital is not different from unity at the 95 percent significance level. Of course, we would expect five percent of the industries studies to exceed these confidence bounds by chance if all industries exhibited true constant returns.

Most of these studies are objectionable, however, because they use industry-aggregate, rather than the more proper plant, or firm, data to test for scale economies. But constant returns still show up when the data are disaggregated to the plant level and tested with Cobb-Douglas and CES functions (Klotz). Another problem with the foregoing econometric studies is their rather crude measures of capital services and the price of these services; and, when very sophisticated measures of the price of capital services are used the simple Cobb-Douglas is reaffirmed at the cost of assuming constant returns (Jorgenson quoting Berndt).

Despite the simplicity and near-unanimity of the econometric production function results the nagging suspicion has remained that there are substantial economies of scale, and so other ways of measuring them have been employed. Engineers in the process industries, such as petroleum refining, not only believe in economies of scale but even employ a rule of thumb, the famous 0.6 rule, to predict that output can be doubled by increasing capital costs by only 60 percent. Something like this rule does hold true

in process industries, probably because capital is proportional to the surface area of the metal inputs employed (pipelines, blast furnaces, etc.) while output is proportional to the volume of the equipment (Haldi and Whitcomb; Bruni). However, this rule may hold only over a limited range of output because surface shells must eventually be strengthened as volume expands, so that capital may be almost proportional to volume as production rises to very high levels. For example, Japanese blast furnaces are so large that they have apparently exhausted any economies of scale achievable from the 0.6 rule (Gold). In any event, the rule gives us the output-capital elasticity, not the output-labor elasticity, and their sum is necessary to compute the degree of returns to scale when both inputs are considered (as they are in the production function approach).

The cost-function method implicitly includes all inputs because it regresses total cost (or average cost) against a curvilinear, usually quadratic, function of output to test whether average cost falls as output expands. If it does, this is evidence favoring economies of scale. The pre-1963 evidence is surveyed by Walters. These types of cost studies all founder though on the hard problem of measuring the cost of capital services. This cost depends in a complicated way upon the interest rate, depreciation rate, rate of change in capital goods prices, and the tax structure (Jorgenson and Hall). Despite these complications the more careful cost studies have found increasing returns to scale in industries with the best data. Unfortunately, these have also been industries (public utilities) where common sense tells us that the technology allows increasing returns. So we cannot assume that other industries necessarily experience increasing returns just because the utilities do.

The survivor method is a brilliant short-cut through the complexities of measuring for scale economies. By measuring the probability of survival in various size classes it picks the class with the highest probability as being the most efficient. This implies that there are scale economies and they are maximized in the size range so discovered. But the problem is that we are not told the elasticity of total cost with respect to output so we cannot calculate the cost savings from moving toward this target size. Therefore, although the survivor method tells us there are economies of scale, it gives us no way of computing the cost savings from a reshuffling of production from suboptimal plants to those with the lowest cost of production. The reader is referred to Rees for a recent application of the survivor technique.

Ireland, Briscoe and Smyth offer a novel way to estimate returns to scale. Their approach combines the rigor of production functions with the simplicity introduced by way of a brilliant short-cut. They argue that the short-run demand function for labor really measures long-run returns to scale because capital utilization changes in proportion to labor in the short-run. Thus, going further, they suggest that fluctuation in labor is a good proxy for fluctuations in all inputs, and so the output response to this oscillation reveals the degree, if any, of increasing returns to scale. In traditional practice, a time series on manhours (or employment) is regressed against a comparable time series on output, lagged manhours and a time trend (to capture technical change). The short-run elasticity of labor relates the change in labor over one time period to the change in output. However, we cannot be sure this is the true scale elasticity since the implicit change in capital utilized may be strained. For example,

machines can be overworked for a short time but continued use at a feverish pace will lead to rapid depreciation and eventual breakdown. Thus, a better measure of scale economies should be the long-run elasticity of labor to output: the full response of labor, allowing for all lagged responses to occur, to changes in output. Unfortunately for the method, Sims finds this long-run elasticity to be insignificantly different from unity, with the full response taking place within six months of the change in output. This suggests an absence of economies of scale for the sectors studied by Sims. The expansion of this method to more detailed industry breakdowns is hampered by a lack of good time series data on physical output. For example, Klotz and Kelly were able to examine only four four-digit industries. The method will come into greater use when better and more extensive price indexes are available for deflating the value of goods produced, thus creating a proxy for a physical output series.

Students of industrial organization cut through econometric complexities and data shortages by creating data of their own through the use of extensive interview questionnaires. These research projects are few in number because they are much more expensive than the computer-assisted econometric manipulation of existing numbers. The most extensive recent studies are by Scherer, et. al. and Pratten. Teitel also conveniently quotes a study by the United Nations.

Scherer, et. al. use the concept of minimum optimum scale while Pratten uses almost the same thing but calls it the minimum efficient scale. The idea is to find the level of output at which average costs either reach their minimum or else stop falling perceptibly. Previous researches point to a range of falling average costs up to some level of output, the minimum

optimal scale, and then a fairly constant average cost for production in excess of this level. So it is of interest to identify the output level at which minimal optimal scale (MOS) commences and also to estimate the elasticity of average costs with respect to output below this level. This elasticity is less than zero if increasing returns to scale occur. A precise estimate of returns requires information on average costs at several widely spaced intervals of output. This contrasts with the econometric approach, whose time series estimates are generated by observing rather narrow intervals of output variation through time. The lack of variation may account for the tendency of such studies to find slight increasing returns to scale, with the difference from constant returns being too minor to be statistically significant. Wider output variation may, as in the interview approach, turn up significant returns to scale.

Scherer examines twelve rather different industries to identify their MOS and to compute the percentage rise in average costs if production is only one-third the MOS. For the United States in 1965 Scherer finds that the Portland Cement industry exhibited the strongest increasing returns to scale of the twelve examined, while nonrubber shoes and cigarettes displayed essentially constant returns. Detailed results are given in Table 1.

Table 1

Percentage Increase in Average Costs at One-Third Minimum Optimal Scale of Plant

Industry	Percentage Increase
Beer Brewing	5.0
Cigarettes	2.2
Cotton & Synthetic Broad-Woven Fabrics	7.6
Paints	4.4
Petroleum Refining	4.8
Nonrubber Shoes	1.5
Glass Bottles	11.0
Portland Cement	26.0
Integrated Steel	11.0
Antifriction Bearings	8.0
Refrigerators	6.5
Auto Batteries	4.6

Clearly, these percentage increases in average costs would be difficult to discern in an econometric investigation in which output varies by much less than 200 percent (the percent by which MOS exceeds (1/3) MOS). Put another way, only three of the twelve industries would experience a fall in average costs exceeding 10 percent, even if output were tripled.

The Pratten study of industry in the United Kingdom is more wide ranging than Scherer's investigation of U.S. firms. And Pratten finds a greater incidence of increasing returns to scale, some of which are quite substantial. His results are summarized in Table 2. He computes the percentage increase in unit costs at one-half MOS (rather than at one-third as in Scherer) and finds highly significant increasing returns to scale in Newspapers, Hardback Books, Dyes and Aircraft. Somewhat smaller increasing returns appear in Chemicals, Bread, Portland Cement, Steel, Cylinder Block Castings, and Electric Motors. The results of Scherer

and Pratten are roughly consistent for Oil Refining, Steel, and (perhaps) Portland Cement. The result for Aircraft in the U.K. agrees with other studies that find a 20 percent fall in unit cost if output is doubled (Hartley).

Table 2

Percentage Increase in Average Costs at
One-Half Minimum Efficient Scale

Industry	Percentage Increase	Minimum Efficient Scale
Oil Refining	5	10 mill. tons per year
Chemicals	9	300,000 tons per year
Dyes	22	Exceeds U.K. production
Bread	15	30 sacks of flour per hour
Portland Cement	9	2 mill. tons per year
Bricks	25	25 mill. bricks per year
Steel	5-10	9 mill. tons per year
Cylinder Block Castings	10	50,000 tons per year
Automobiles	6	500,000 per year
Aircraft	20+	50+ aircraft
Machine Tools	5	Exceeds U.K. production
Diesel Engines (1-100 h.p.)	4	100,000 units per year
Marine Diesels	8	100,000 h.p.
Turbo Generators	5	4 per year
Electric Motors	15	60% of U.K. production
Electrical Appliances	8	500,000 per year
Electronic Capital Goods	8	1,000 units
Newspapers	20+	30% of U.K. production
Hardback Books	36	10,000 copies
Plastic Products	Substantial	100% of U.K. production

Although Scherer and Pratten find similar scale economies for the same industries in the U.S. and the U.K., the United Nations study surveyed by Teitel suggests stronger economies. Teitel quotes the elasticity, S, of total cost to output for nine industries. Using the fact that S-1 is the elasticity of average cost with respect to output, we compute:

Table 3

Elasticity of Average Costs to Output, S-1

Industry	S-1
Aluminum	-.20
Acetylene	-.31
Ammonium Nitrate	-.35
Beer Glass Bottles	-.30
Cement	-.48
Ethylene	-.46
Polyvinylchloride	-.47
Rolled Steel	-.29
Fine Cotton Textiles	-.24

These elasticities can be matched against Pratten's "percentage increase in average costs if output is halved" by noting that such a 50% fall in output will, for example, cause a 10% rise in the average cost of producing Aluminum (because Aluminum has S-1 = -.20). The general formula for the rise in average cost if production is halved is the absolute value of (S-1)/2. Thus, we ignore the minus sign in *Table* 3 and halve the numbers in the "S-1" column to obtain comparisons with Pratten's results in Table 2. The average S-1 in Table 3 is -.34, so we obtain +.17 by our formula for conversion. This .17 generally exceeds Pratten's estimates: i.e., 14 of the 20 industries in Table 2 have percentages less than .17 (and this Table only reports the higher of Pratten's findings).

We conclude that the industry studies reveal substantial economies of scale in some industries, moderate economies in others, and a general tendency toward economies in industries where common sense suggests that they exist (e.g., Airplanes, Newspapers, and Books). However, another finding of Pratten was that the MOS increased through time as new technology, embodied in the latest vintages of capital equipment, and learning from

experience, combined to expand the lowest-cost scale of output. This suggests that dynamic forces increase the range over which economies can be experienced and also may change the elasticity, S, of average costs with respect to output. To capture these forces we must turn away from the static concept of economies of scale, in which the level of technology is held constant, and begin to investigate the evidence on learning-by-doing, or learning curves, in which changes in scale and in technology are both summarized in one measure relating the change in unit costs and the change in output.

LEARNING BY DOING

It has often been noted that the unit cost of production falls with increasing experience with production in certain industries. The most noticeable example appears in the aircraft industry (Asher; Levenson and Barro; Hartley), although a variety of other industries appear as well (Baloff). Learning has even been found using an aggregate production function for the U.S. (Sheshinsky). The industry studies use variations on the basic model $Y = aX^b$, where a and b are constants, Y is output per unit of input, and X is the cumulative output of the product over some time period stretching back into the past. The input may be labor, or capital, or materials, or some composite input; but in most cases it is labor alone. Also, Y may refer to the average, or the marginal output per unit of input. However, this complication disappears if X exceeds 20-30 units because average and marginal learning curves tend to become parallel after 20 units are produced with this learning model. The model is also often inverted, making Y the unit input requirement, in which case b is a negative constant. It is

often of interest to find the percentage decline in unit labor requirements, for example, if cumulative output is doubled. The decline is $1 - a(2X)^b/a(X)^b = 1 - 2^b$.

We will discuss the industry results of Baloff before turning to the more specialized aircraft, and other military, studies. Baloff defines Y as output per manhour so that b is positive. He studies a number of production runs in two steel plants, two runs in a glass products plant, and one run each in an electrical products and a paper products plant. His estimates of b, using ordinary least squares (OLS) to fit Y and X values, appear in Table 4. The learning curve fitted well in all cases (goodness-of-fit statistics are omitted from the Table for simplicity), if we assume an absence of serial correlation in the residuals from the fitted equation $\hat{Y} = \hat{a}\, X^{\hat{b}}$. Baloff does not test for serial correlation so we cannot tell if his estimated standard deviations of $\hat{b}$ are biased downward (as they would be if the residuals were serially correlated). And if they were biased downward then the various estimates of b, over the several production runs, might not be significantly different. In this case, some underlying b value might be generating the variety of estimated bs due simply to sampling variation, thus strengthening the argument for some magic constant of nature in learning. But there would be a catch to this: the learning curve would not fit as well as indicated by the OLS equation. We would need to apply generalized least squares (GLS) to obtain an unbiased estimate of goodness-of-fit (Theil), and this fit would be less good than implied by the naive OLS approach. Unfortunately, all studies of learning curves seem to use OLS so all of their goodness-of-fit statistics are suspect, until they test for (and reject) serial correlation. The theoretical case for serial correlation

is strengthened if we assume that the basic relation is not $Y = aX^b$, but rather a log-linear relation between the <u>percentage changes</u> in Y and X. The presence of serial correlation would explain the inability of Alchian's $Y = aX^b$ learning curves to accurately predict future labor requirements, despite fitting (spuriously?) well to past data. However, despite our reservations about the unbiasedness of the <u>standard deviations</u> of $\hat{b}$, we note that serial correlation does <u>not</u> bias $\hat{b}$ itself. Thus we are probably safe in using these $\hat{b}$ estimates, only we should not expect them to predict as well as their goodness-of-fit to past data suggests.

Table 4

Learning Curves in Selected Industries

		Production Runs	b
Steel:	Company A		
	Plant I	1-8	.17, .20, .24, .26, .25, .27, .43, .76
	II	9-11	.22, .19, .34
	III	12-14	.23, .25, .48
	IV		.30
	V		.68
	VI		.29
	Company B	1-7	.17, .18, .10, .35, .23, .49, .25
Glass Products			.60, .35
Electric Products			.24
Paper Products			.16

With these statistical caveats in mind we note from Table 4 that the estimates of <u>b</u> tend to cluster somewhat in the range .20-.30 for the various industries. In this model case, a doubling of cumulative output X would cause a 20-30 percent rise in output per manhour (which is a 20-30 percent decline in unit labor requirements). In other words, unit labor requirements would decline to .70-.80 of their initial value if cumulative

output were to double. We cast Baloff's results in this framework, stressing the values .70-.80, which we denote by S, so as to compare them directly with the many studies of S in the aircraft industry.

A number of studies have reached the conclusion that S is approximately .75-.80 in the aircraft industry. Hartley finds .80 for U.K. production and Levenson and Barro find S=.75 for U.S. experience. The U.S. result had a standard deviation of .03 over 25 aircraft. There is also evidence, however, that S (and hence _b_) is not a constant over all ranges of output of a particular plane, that S approaches unity (_b_ approaches zero) at some large cumulative output (Asher), and that S is thus not as reliable in predicting unit labor requirements outside the range of past data as it appears (Alchian). Furthermore, Large and Gillespie find unit costs are a function not only of aggregate output, but also of aircraft weight and speed in a number of studies of U.S. data. This relation is also true in the U.K. (Hartley). However, since Levenson and Barro found narrow variation in _b_ (and S) over 25 U.S. aircraft, the complexities of weight and speed apparently influence only _a_ in the equation $Y = aX^b$. In this case, we can predict the _percentage_ fall in unit labor requirements for a given percentage change in X, and _a_ does not enter into this prediction.

Further evidence on the robustness of S=.80 comes from cost estimates for the F-16 fighter plane. Robinson reports a unit cost of production of $4.63 million if 650 planes are built in the U.S. But costs fall to $4.24 million per plane for 1,000 units. Thus, unit costs fall by nine percent due to a 54 percent increase in aggregate output. At this rate a doubling of output would lead to a 17 percent decline in unit costs, or an S = .83.

Learning curves for other types of weapons are not so well established but we do know that S = .70-.80 for ships (Oi), .85 for helicopters (Oi) and .89-.97 for materials (Hartley), and .88-.92 for electrical appliances (Oi). These values imply more learning in ship building than in aircraft production, probably because fewer of the former are built. This reasoning also would explain, due to diminishing learning effects in longer production runs, the higher S values for electrical appliances. These appliances may have a similar production pattern to military items such as missile system components. Smith reports the following S values in the Army Life Cycle Cost Model for Tactical Missile Systems: propulsion, .92; semi-active or passive radar guidance systems, .85; control systems, .85; launcher mechanical assembly, .85.

Learning curves for other types of weapons might be rather heroically inferred from data in Gervasi. He quotes unit procurement costs on a wide variety of weapons in various years. Most of the time these costs rise through time due to inflation and to design modifications. But in seven cases these costs fall, bucking the trend of inflation. We might then infer that learning effects are at least as great as the falling costs for these seven weapons. Because Gervasi also reports current production quantities and the total produced to date of each weapon, we can compute S conservatively (i.e., assuming no cost inflation between the two years compared) between two adjacent years. We find S values as follows: Fairchild-Republic A-10A Close Air Support Aircraft, .94; M-60 A1 Main Battle Tank, .90; XM 198 155 mm artillery howitzer, .88. The A-10A support (combat) aircraft has a "too high" S value compared to the usual .80 found for aircraft in other studies cited above. So inflation from 1977 to 1978

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can be blamed for this discrepancy, although there may well be other reasons. The Main Battle Tank value (S=.90) may therefore be even lower, but at least this figure agrees with Pratten's estimate of returns to scale in the very similar Automobile industry.

We can also infer S values for four missiles from Gervasi's data. They have longer production runs than the three weapons just discussed. Again comparing costs and outputs of adjacent years we find S = .84, .85, .93 and .93 for the four missiles (they are, respectively, the AGM-65B Maverick, AIM-9L Sidewinder, AIM-7F, and FIM-92A Stinger).

Summing up the military studies of S, it seems that S is greater the larger the production target for the weapon. Thus, ships with the lowest target (compared to missiles with their target of thousands) have the smallest S, while missiles have the highest target and the highest S. Aircraft fall in the middle range with respect to volume of production and thus experience an S near .80. Extending this argument, we would expect very little learning in the production of ammunition but a great deal in the production of an Airborne Warning and Control System (AWACS). Conservatism suggests an S=.90-.95 for weapons produced in the tens of thousands (such as missiles), S=.90 for weapons in the thousands (e.g., tanks), S=.80 for weapons in quantities of hundreds (the famous aircraft case), and S=.70-.75 for weapons in quantities of less than one hundred (such as ships). This pattern of declining S with increasing quantity is consistent with Asher's findings on lengthier aircraft production runs.

COST SAVINGS DUE TO SCALE AND LEARNING EFFECTS

Assume we have the price and output quantities of a product, each year, produced by a number of different producers. And assume the price is set as a constant markup above unit costs of production. To be specific, let the product be the F-16 combat fighter plane. It would be useful to compute the cost savings resulting from specializing production at the lowest cost site (such as a nation for the F-16). The total production at other (nation) sites is added to that at the lowest cost site. This results in a specified percentage increase in annual output at this site; it also implies a specified percentage increase in cumulative output (i.e., the sum of past output at the site). The former percentage can be used to compute unit cost savings resulting from economies of scale; the latter percentage allows us to calculate the cost reductions stemming from the learning curve. We can thus estimate the unit cost savings in two ways if we have a measure of both scale economies and learning curves in the production of this output.

Assuming Y is unit costs we use $Y = a\,Q^b$ to compute savings due to scale economies: Percentage change in Y = $\underline{b}$ x(Percentage change in Q). Annual budget data should reveal current Y and Q so it is a simple matter to compute the percentage change in unit costs Y, if we have an estimate of scale economies $\underline{b}$. The problem is that evidence on $\underline{b}$ is very sketchy for defense industries. Most studies of scale economies examined above

referred to non-defense industries. However, Pratten (Table 2) concludes that a halving of aircraft production will force up unit costs by 20 percent. Conversely, a doubling of output from this lower level (back up to the optimal-scale output) will reduce unit costs by 16 percent (20/(100+20)). This suggests a b in the range .15-.20, with a negative sign of course. But scale-economy estimates are lacking for other defense products, such as missiles.

We could fill the gap of missing scale parameters by assuming they vary in proportion to the variation observed in the learning-curve parameter S. Thus, ships and planes (with S = .70-.80) would be assigned the greatest scale economies (with b = .15-.25); missiles (with S near .90-.95) would get b = .05. The intermediate case of tanks (S = .90) would have b = .10. This accords with common sense because we saw that S was lower, hence b higher in absolute value, the shorter the production run. And shorter runs seem to suggest a greater potential for economies of scale. Thus, at some risk of misestimating the true b for a weapon, we can compute the unit cost savings from reshuffled production using only a knowledge of the current unit cost (or price) and the current percentage change in annual output required to achieve specialization. This all follows from the unit cost equation $Y = a\ Q^b$.

However, we can do better than this if we also know cumulative output to date of a weapon at a national site. In this case, the increase in annual output to achieve specialization (at this lowest cost site) can be expressed as a percentage of cumulative output X, and the percentage change in X can then be used to predict the fall in unit costs (and prices) using the learning curve $Y = a\ X^b$. This curve implies that the percentage

change in unit costs = b x (Percentage change in the cumulative output X). We have direct evidence on b in this equation because it is a simple transformation of the learning parameter S which we found to vary between .70 and .95, depending on the specific weapon in question.

The method outlined above can be employed with several variations. Future projections of output (based on replacement needs plus desired increase in the stock of weapons) can be used to obtain the percentage increase in future output and this can be used to compute the future cost savings from specialized production. The exercise could also be repeated assuming specialization of production at the current dominant site, if it differs from the lowest cost site. We could also consider the effect of consolidating the production of similar, or substitute weapons, into one common model and producing this one model at the lowest-cost site. This variant of the analysis would reveal the largest cost savings because consolidation would cause the largest output increases at the low-cost site and this would lead (either through scale economies or learning) to the greatest absolute declines in unit costs. To avoid ambiguity in defining the lowest-cost site, it should be the lowest-cost site after consolidation of production, not the lowest-cost site before consolidation, because the latter criterion would give the advantage to the current dominant (largest scale) producer due to the presence of scale effects and learning.

A final caveat concerns changes in scale of operation at a chosen site. If a previously small-scale site is chosen then consolidation will dictate a large increase in output and the employment of inputs in the nation chosen. And, if this nation faces bottlenecks such as a shortage of skilled labor (either due to near-full employment or a lack of appropriate scientific training) then we can be sure that input prices will rise, relative to other

nations, as production expands at the site. This inflation will cut into the cost savings from specialization. In addition, if the process of specialization over all weapons turns out to reallocate production among nations then the gainers will, ceteris paribus, tend to experience higher rates of inflation (due to the increase in aggregate demand) and their currency will also tend to appreciate (due to the shift in demand for their products). Both of these effects will raise the currency cost of the weapons to foreign buyers, again eating into the cost savings achieved by specialization. However, these currency costs will be trivial if the reallocation of production is minor.

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